Suthers, D. D., Dwyer, N., Medina, R., & Vatrapu, R. (2010). A framework for conceptualizing, representing, and analyzing distributed interaction. International Journal of Computer Supported Collaborative Learning, 5(1), 5-42.

A Framework for Conceptualizing, Representing, and Analyzing Distributed Interaction

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Abstract: The relationship between interaction and learning is a central concern of the learning sciences, and analysis of interaction has emerged as a major theme within the current literature on computer-supported collaborative learning. The nature of technology-mediated interaction poses analytic challenges. Interaction may be distributed across actors, space, and time, and vary from synchronous, quasi-synchronous, and asynchronous, even within one data set. Often multiple media are involved and the data comes in a variety of formats. As a consequence, there are multiple analytic artifacts to inspect and the interaction may not be apparent upon inspection, being distributed across these artifacts. To address these problems as they were encountered in several studies in our own laboratory, we developed a framework for conceptualizing and representing distributed interaction. The framework assumes an analytic concern with uncovering or characterizing the organization of interaction in sequential records of events. The framework includes a media independent characterization of the most fundamental unit of interaction, which we call *uptake*. Uptake is present when a participant takes aspects of prior events as having relevance for ongoing activity. Uptake can be refined into interactional relationships of argumentation, information sharing, transactivity, and so forth. for specific analytic objectives. Faced with the myriad of ways in which uptake can manifest in practice, we represent data using graphs of relationships between events that capture the potential ways in which one act can be contingent upon another. These *contingency graphs* serve as abstract transcripts that document in one representation interaction that is distributed across multiple media. This paper summarizes the requirements that motivate the framework, and discusses the theoretical foundations on which it is based. It then presents the framework and its application in detail, with examples from our work to illustrate how we have used it to support both ideographic and nomothetic research, using qualitative and quantitative methods. The paper concludes with a discussion of the framework's potential role in supporting dialogue between various analytic concerns and methods represented in CSCL.

Keywords: interaction analysis, distributed learning, uptake, contingency graphs

Introduction

Researchers, designers, and practitioners in the learning sciences and allied fields study a variety of technology-supported settings for learning. These settings may include tightly coupled small group collaboration, distributed cooperative activity involving several to dozens of persons, or large groups of loosely linked individuals. Examples include asynchronous learning networks (Bourne, McMaster, Rieger, & Campbell, 1997; Mayadas, 1997; Wegerif, 1998), knowledge building communities (Bielaczyc, 2006; Scardamalia & Bereiter, 1993), mobile and ubiquitous learning environments (Rogers & Price, 2008; Spikol & Milrad, 2008), online communities (Barab, Kling, & Gray, 2004; Renninger & Shumar, 2002), and learning in the context of "networked individualism" (Castells, 2001; Jones, Dirckinck-Holmfeld, & Lindstrom, 2006). These settings are diverse in many ways, including the degree of coupling between participants' activities, varying temporal and social scales, and the supporting technologies used. However, they all rely on interaction to enhance learning. "Interaction" is used here in a broad sense, including direct encounters and exchanges with others and indirect associations via persistent artifacts that lead to individual and group-level learning. The common element is how participants benefit from the presence of others in ways mediated by technological environments.

The distributed nature of interaction in technology-mediated learning environments poses analytic challenges. Interaction may be distributed across actors, media, space, and time. Mixtures of synchronous, quasi-synchronous, and asynchronous interaction may be included, and relevant phenomena may take place over varying temporal granularities. Participants may be either co-present or distributed spatially, and often multiple media are involved (e.g., multiple interaction tools in a given environment, or multiple devices). Furthermore, the data obtained through instrumentation comes in a variety of formats. There may be multiple data artifacts for analysts to inspect and share, and interaction may not be immediately visible or apparent, particularly when interaction that is distributed across media is consequentially recorded across multiple data artifacts. Interpretation of this data requires tracing many individual paths of activity as they traverse multiple tools as well as identifying the myriad of occasions where these paths intersect and affect each other.

Other analytic challenges are also exacerbated by technology-mediated interaction. Human action is contingent upon its context and setting in many subtle ways. These contingencies take new forms and may be harder to see in distributed settings. Interpreting nonverbal behavior is also a challenge. When users of a multimedia environment manipulate and organize artifacts in ways implicitly supported by the environment, it may be difficult to determine which manipulations are significant for meaning making. The large data sets that can be collected in technology-mediated settings lead to tensions between the need to examine the sequential organization of interaction within an episode and the need to scale up such analyses to more episodes and larger scale organization. We are challenged to understand phenomena at multiple temporal or social scales, and to understand relationships between phenomena across scales (Lemke, 2001). See Suthers and Medina (in press) for further discussion of these analytic challenges.

We have encountered many of these challenges in our own research. This research includes a diverse portfolio of studies of co-present and distributed interaction, via various synchronous and asynchronous media, and at scales including dyads, small groups, and online communities. Our research methods have included experimental studies (Suthers & Hundhausen, 2003; Suthers, Vatrapu, Medina, Joseph, & Dwyer, 2008; Vatrapu & Suthers, 2009), activity-theoretic and narrative analysis of cases (Suthers, Yukawa, & Harada, 2007; Yukawa, 2006), adaptations of conversation analysis (Medina & Suthers, 2008; Medina, Suthers, & Vatrapu, 2009), and hybrid methods (Dwyer, 2007; Dwyer & Suthers, 2006). Through the diversity of our work, we have come to appreciate that the analytic challenges outlined above are not specific to one setting or method, and we have been motivated to find a solution that gives our work conceptual coherence rather than solutions that are specific to one type of environment and/or type of analysis.

In order to address these challenges in a principled way, we developed the *uptake analysis framework* for conceptualizing, representing, and analyzing distributed (technology-mediated) interaction. We offer that framework in this paper in hopes that some aspects of it may also be useful to others. The representational foundation of this framework is an abstract transcript notation—the *contingency graph*—that can unify data derived from various media and interactional situations and has been used to support multiple analytic practices. The conceptual foundation of this framework includes *uptake* as a fundamental building block of interaction, and the basis for construing interaction as an object of study. Like any analytic framework, the uptake analysis framework carries theoretical assumptions. However, it is not primarily a theory: It provides a theoretical perspective on how to look at interaction, but it does not provide explanations or make predictions. Nor is it primarily a single method: It is a coordinated set of concepts and representations with associated practices that support multiple methods of analyzing distributed interaction. These distinctions are why we call it a "framework."

This paper begins by elaborating on our motivations and requirements in the next section. The following section presents the conceptual, empirical, and representational foundations of the uptake analysis framework. We then detail practical aspects of applying the framework, and provide selected examples from our work to illustrate how it supports several types of analyses with multiple data sources. After a summary and discussion of limitations and extensions, we conclude with a discussion of its potential role in supporting dialogue between various analytic concerns and practices represented in CSCL.

Motivations and Requirements

This work had its origins in our recognition of the analytic limitations of our prior work and our attempts to reconcile the strengths and weaknesses of two methodological traditions. The first author's earlier research program tested hypotheses concerning "representational guidance" for collaborative learning in experimental studies where participants' talk and actions were coded according to categories relevant to the hypotheses, and frequencies of these codes were compared across experimental groups (Suthers & Hundhausen, 2003; Suthers, Hundhausen, & Girardeau, 2003; Suthers et al., 2008). While these studies suggested that representational influences were present, the statistical analyses as they were conceived did little to shed light on the actual collaborative processes involved and, hence, of the actual roles that the representations played. To address this problem, we began several years of analytic work to expose the practices of mediated collaborative learning in data from our prior experimental studies, beginning with microanalytic approaches inspired by the work of Tim Koschmann, Gerry Stahl, and colleagues (Koschmann et al., 2005; Koschmann, Stahl & Zemel, 2004). In an analysis undertaken in order to understand how knowledge building was accomplished via synchronous chat and evidence mapping tools, we applied the concept of *uptake* to track interaction distributed across these tools (Suthers, 2006a). Subsequently, we began analyzing asynchronous interaction involving threaded discussion and evidence mapping tools (Suthers, Dwyer, Vatrapu, & Medina, 2007). In conducting this work, we encountered limitations of microanalytic methods, discussed below. In response, we developed our analytic framework to handle the asynchronicity and multiple workspaces of our data, and with hopes of scaling up interaction analysis to larger data sets (Suthers, Dwyer, Medina, & Vatrapu, 2007). Concurrently, we were pursuing a separate line of work on analyzing participation in online communities through various artifact-mediated associations (Joseph, Lid, & Suthers, 2007; Suthers, Chu, & Joseph, 2009). This work further motivated the development of a way of thinking about mediated interaction that would inform and unify the diverse studies that we were conducting. In this section, we discuss several recurring concerns that arose, including addressing the respective strengths and weaknesses of statistical and micro-genetic interaction analyses, and handling the diverse data derived from distributed settings in a manner that supports multiple approaches to understanding the organization of interaction.

Statistical Analysis

Many empirical studies of online learning follow a paradigm in which contributions (or elements of contributions) are annotated according to a well-specified coding scheme (e.g., De Wever, Schellens, Valcke, & Van Keer, 2006; Rourke, Anderson, Garrison, & Archer, 2001), and then instances of codes are counted up for statistical analysis of their distribution (e.g., across experimental conditions). Research in this tradition is nomothetic, seeking law-like generalities, and, in particular, is typically oriented toward hypothesis testing. This approach has significant strengths. Coding schemes support methods for quantifying consistency (reliability) between multiple analysts. Well-defined statistical methods are available for comparing results from multiple sources of data such as experimental conditions and replications of studies. Also, it is straightforward to scale up statistical analysis by coding more data.

A limitation is that these practices of coding and counting for statistical analysis obscure the sequential structure and situated methods of the interaction through which meaning is constructed (Blumer, 1986). Coding assigns each act an isolated meaning, and, therefore, does not adequately record the indexicality of this meaning or the contextual evidence on which the analyst relied in making a judgment. Frequency counts obscure the sequential methods by which media affordances are used in particular learning accomplishments, making it more difficult to map results of analysis back to design recommendations. Another limitation is that in common practice statistical significance testing is applied to preconceived hypotheses to be tested rather than oriented toward discovery. An analysis of interaction might help researchers discover what actually happened that led to the statistical results—whether statistical significance was obtained as predicted, obtained in patterns that were not predicted, or absent. Such an analysis is only possible if the data was recorded in a form that retains its interactional structure. Our framework is intended to support statistical analysis in two ways: by providing sequential structures (as well as single acts) that can be coded and counted, and by recording these structures for interaction analysis that helps make sense of statistical results.

Sequential Analysis

Several analytic traditions find the significance of each act in the context of the unfolding interaction. These traditions include Conversation Analysis (Goodwin & Heritage, 1990; Sacks, Schegloff, & Jefferson, 1974), Interaction Analysis (Jordan & Henderson, 1995), and Narrative Analysis (Hermann, 2003). Some of these traditions (especially the first two cited) draw upon the assertion that the rational organization of social life is produced and sustained in participants' interaction (Garfinkel, 1967). A common practice is *microanalysis*, in which short recordings of interaction are carefully examined to uncover the methods by which participants accomplish their objectives. Microanalysis is becoming increasingly important in computer-supported collaborative learning because a focus on accomplishment through mediated action is necessary to truly understand the role of technology affordances (Stahl, Koschmann, & Suthers, 2006). For examples applied to the analysis of learning, see Baker (2003), Enyedy (2005) Koschmann and LeBaron (2003), Koschmann et al. (2005), Roschelle (1996), and Stahl (2006, 2009).

Microanalysis has somewhat complementary strengths and weaknesses compared to statistical analysis. It documents participants' practices by attending to the sequential structure of the interaction, producing detailed descriptions that are situated in the medium of interaction. Yet analyses are often time consuming to produce, and are difficult to scale up. As a result, microanalysis is usually applied to only a few selected cases, leading to questions about representativeness or "generality" (but see Lee & Baskerville, 2003, for arguments against basing generalization solely on sampling theory). Microanalysis is most easily and most often applied to episodes of synchronous interaction occurring in one physical or virtual medium that can be recorded in a single inspectable artifact, such as a video recording or replayable software log. Distributed interaction may occur in more than one place, and learning may take place over multiple episodes, problematizing approaches that assume that a single analytic artifact recorded in the medium of interaction is available for review and interpretation.

The family of methods loosely classified as *exploratory sequential data analysis* (ESDA, Sanderson & Fisher, 1994) provide a collection of operations for transforming data logs into representations that are successively more suitable for analytic interpretation. In Sanderson and Fisher's (1994) terms, the operations are chunking, commenting, coding, connecting, comparing, constraining, converting, and computing. ESDA draws on computational support for constructing statistical and grammatical models of recurring sequential patterns or processes (e.g., Olson, Herbsleb, & Rueter, 1994). Because of this computational support, ESDA can be scaled up to large data sets while still attending to the sequential structure of the data. On these points, ESDA compares favorably to the respective limitations of microanalysis and "coding and counting." However, like statistical analysis, computational support risks distancing the analyst from the source data. Another limitation is that many of the modeling approaches use a state-based representation that reduces the sequential history of interaction to the most recently occurring event category. Reimann (2009) presents a cogent argument for basing process analysis on an ontology of events rather than variables, and describes Petri net process models (from van der Aalst & Weijters, 2005) that capture longer sequential patterns than state transitions. These approaches will be discussed further at the end of the paper. Our framework is intended to support both distributed extensions of microanalysis and ESDA approaches.

Media Generality

Some analytic traditions use units of analysis and data representations that are based on the interactional properties of the media under study. Much of the foundational work in sequential analysis of interaction has focused on spoken interaction. The difficulty of speaking while listening and the ephemerality of spoken utterances constrain communication in such a manner that turns (Sacks et al., 1974) and adjacency pairs (Schegloff & Sacks, 1973) have been found to be appropriate units of interaction for analysis of spoken data. These units of analysis are not as appropriate for interactions in media that differ in some of their fundamental constraints (Clark & Brennan, 1991). For example, online media may support simultaneous production and reading of contributions, or may be asynchronous, and contributions may persist for review in either case. Consequentially, contributions may not be immediately available to other participants or may become available in unpredictable orders, and may address earlier contributions at any time (Garcia & Jacobs, 1999; Herring, 1999). It is not appropriate to treat computer-mediated communication as a degenerate form of face-to-face interaction, because people use attributes of new media to create new forms of interaction (Dwyer & Suthers, 2006; Herring, 1999). Because conceptual coherence of a set of contributions can be decoupled from their temporal or spatial adjacency, our framework is based on a unit of interaction that does not assume adjacency or other media-specific properties.

Similarly, properties of distributed interaction place different demands on representations of data and analytic structures. Because technology-mediated interaction draws on many different semiotic resources, analysis of interactional processes must reassemble interaction from the separate records of multiple media, while also being sensitive to the social affordances of each specific medium being analyzed to distinguish their roles. A framework for analysis of mediated interaction must be *media agnostic*—independent of the form of the data under analysis—yet *media aware*—able to record how people make use of the specific affordances of media. This is required to allow analysis to speak to design and empirically drive the creation of new, more effective media. Our framework provides a means of gathering together distributed data into a single representation of interaction that does not make assumptions about media properties but indexes back to the original media records.

Impartiality

Any analytic program must be based on theoretical assumptions concerning what kinds of questions are worthwhile and what counts as data. Transcripts carry some of these theoretical assumptions (Ochs, 1979), but this bias is not a fait accompli: We can actively shape the role of transcripts as representations in our analytic practices (Duranti, 2006). We believe that analytic representations should minimize assumptions concerning the answers to the research questions posed, limiting assumptions to those necessary to ask those questions in the first place. This desideratum applies to basic analytic constructs such as the choice of units of data to be analyzed (segmentation) and the fundamental relationships by which we characterize interaction. Because we are analyzing and theorizing about interaction from diverse settings, we want our data and analytic representations to support variable and multi-leveled granularities, and our basic unit of interaction to be neutral toward possible interpretations of that interaction.

In summary, the considerations discussed in this section led us to address our practical analytic problems by developing an approach that records the sequential and situational context of activity so that an account of the interactional construction of meaning is possible, and does not pre-specify the interactional properties of the medium of interaction (e.g., synchronicity, availability of contributions and their production, persistence) but records these properties where they exist. Additionally, the approach is sufficiently formalized to enable computational support for analysis (including statistical and sequential analysis) and captures aspects of interaction in a manner that impartially informs research questions concerning how the sequential organization of activity leads to learning. The analytic framework we developed to meet these requirements draws on other interaction analysis methods, but uses a generalized concept of the unit of interaction and a data representation that is independent of any particular medium.

The remainder of the paper first describes the conceptual, empirical, and representational foundations for our analytic framework before turning to examples of how it is constructed and used. Readers who prefer to begin with examples are invited to skip to those sections after reading the brief overview section below, but are warned that the examples are presented in terms of the framework they are intended to illustrate, so some prior introduction to this framework is a prerequisite.

The Uptake Analysis Framework

The framework we developed assumes an analytic concern with uncovering or characterizing the organization of interaction in records of events. The framework offers conceptual foundations (units of action and interaction that are inclusive of a range of phenomena in distributed interaction); empirical foundations (observed events and relationships between them that evidence these phenomena); and representational foundations (an abstract transcript that captures this evidence in a unified analytic artifact and that supports multiple analytic practices). These foundations for analysis are presented in detail in this section, after a brief overview.

Overview

The framework is layered to make certain distinctions in analytic practice explicit. Given a data stream of events, analysts select certain events as being of significance for analysis (e_i bottom of Figure 1). Some of the events may be environmentally generated events, and some of the events are points at which actors in the interaction *coordinate* between personal and public realms. Next, the analyst identifies empirically grounded relationships between events that provide potential evidence for interaction. We call these relationships *contingencies*. Contingencies between events are represented in abstract transcripts that we call *contingency graphs*. Contingencies indicate how acts are manifestly related to each other and their environment. The analyst interprets sets or patterns of contingencies as evidence for interaction. We propose the concept of *uptake* as an analytic way station in this process of interpretation. An assertion that there is uptake is an assertion that a participant has taken aspects of prior events as having relevance for ongoing activity. This assertion is made more concrete in ways specific to analytic traditions, interpreting uptake as recognizable activity (top of Figure 1) in a manner that is grounded in specific actions and the relationships between them.

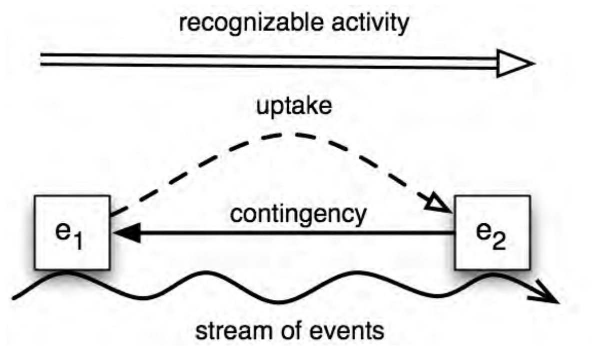


Figure 1. Analytic schema

To summarize, events and contingencies between them are the empirical foundations of the uptake analysis framework; graphs representing events as vertices and contingencies as edges are the representational foundation of this framework; and uptake between coordinations is the conceptual foundation for identifying interaction in this framework. In using the terms "coordination," "contingency," and "uptake," we are collecting together and clarifying concepts about interaction that exist in current theory and analytic practice. These concepts are discussed in more detail below and are summarized in Table 1. We begin with discussion of conceptual foundations, as this motivates the empirical and representational foundations.

Conceptual Foundations: Inclusive Units of Action and Interaction

The conceptual foundations for the framework include concepts of action and interaction that generalize from existing analytic concepts to factor out assumptions about the setting.

Events, acts, and coordination. The framework assumes that analysis begins with records of events that are characterized in terms of observable features such as changes in the environment and their temporal and spatial locales. These events may include *acts*—those events due to the agency of a specified, and for our purposes human, *actor*—and events involving nonhuman *actants* (Latour, 2005).

Many analyses of collaborative learning are particularly interested in acts by which participants coordinate between personal and public realms, including with each other. The term *coordination* is taken from the distributed cognition account of "coordination of [not necessarily symbolic] information-bearing structures" between personal and public realms (Hutchins, 1995, p. 118). Whereas distributed cognition postulates bringing internal and external representations into alignment, the concept of coordination can

Table 1. Summary of Framework Levels and Elements

Empirical Foundation	
Events	Observed changes in the environment
Contingencies	Manifest relationships between events (see Table 2)
Representational Foundation (abstract transcript)	
Vertices	Represent, annotate and index to source data for events
Hyperedges	Represent, annotate and index to source data for contingencies
Conceptual Foundation	
Coordinations	Acts in which an agent coordinates between personal and public realms
Uptake	Taking aspects of other coordinations as having certain relevance for ongoing activity

also be understood as the intentionality that marks the divide between the agency of objects postulated by actor-network theory (Latour, 2005, p. 62ff) and the object-oriented agency of human actors postulated by activity theory (Kaptelinin & Nardi, 2006 section 9.2). However, the framework outlined in this paper does not require assumptions about the nature of the personal realm. We accept that some analytic traditions may identify relevant acts without postulating cognitive representations or inferring intentionality.

Other literature uses the term *contribution*, but we desire a term that does not imply a conversational setting, and that is not biased toward production as the only kind of relevant action. For example, when a participant reads a message the personal realm is brought into coordination with inscriptions in the message, and when the participant writes a message, inscriptions are created in the public realm that are coordinated with the personal realm. In previous writings, we used the term *media coordination*, because all interaction is mediated by physical and cultural tools (Wertsch, 1998), whether in ephemeral media such as thought, vocalizations, and gesture, or persistent media such as writing, diagrams, or electronic representations. The adjective *media* is dropped herein because it is redundant. The concept of coordination is relevant to Vygotsky's developmental view of learning as the internalization of interpsychological functions (Vygotsky, 1978), although these two ideas are at different time scales.

Activity theory postulates three levels of activity: operations, actions, and activity (Kaptelinin & Nardi, 2006, section 3.4). Coordinations correspond most closely to the level of action, lying between events generated at the operational level and the ongoing activity that the analyst seeks to understand. Because of this correspondence, we will use *act* as a synonym for coordination where it simplifies the prose. We use *event* when we wish to include environmentally generated events or refer to the data stream of events before specific events have been analytically selected as constituting coordinations.

Uptake. Interaction is fundamentally relational, so the most important unit of analysis is not isolated acts, but rather relationships between acts. The framework is based on a relationship that underlines the various conceptions of interaction current in the CSCL literature, but abstracts from assumptions about the format or setting of interaction. Although there are many conceptions of how learning is social or socially embedded, each of these forms of social learning is only possible when a participant takes something from prior participation further. We call this fundamental basis of interaction *uptake* (Suthers, 2006a, 2006b). Uptake is the relationship present when a participant's coordination takes aspects of prior or ongoing events as having relevance for an ongoing activity. For example, in a coherent conversation each contribution is interpretable as selecting some aspect of the foregoing conversation, and, by foregrounding that aspect in a given way, bridging to potential continuations of the conversation. Even more explicitly, a reply in a threaded discussion demonstrates the author's selection of a particular message as having certain relevance for participation. But uptake can also be subtler. The aspects taken as relevant can include not only expressions of information, but also attitudes and attentional orientation; and their manifestations may be ephemeral as in speech or persistent as in writing or digital inscriptions. Participants may take up others' ways of talking about the matter at hand, or may mimic representational practices, such as notational conventions or the organization of objects in a workspace. Even the act of attending to another's contribution is a form of uptake. Thus, the concept of uptake supports diverse definitions of "interaction," including any association in which one actor's coordination builds upon that of another actor or actant. Uptake can cross media and modalities. Uptake conceptualizes relationships between actions in a media-independent manner and potentially at multiple temporal or spatial scales.

Uptake is transitive and transformative. Uptake is transitive in the grammatical sense that it takes an object: Uptake is always oriented toward the taken-up as its object. Uptake transforms that taken-up object by foregrounding and interpreting aspects of the object as relevant for ongoing activity: *Objekt* becomes *predmet* (Kaptelinin & Nardi, 2006, chapter 6). Manifestations of this transformed object become available as the potential object of future uptake in any realm of participation in which it is available (as discussed further below). Therefore, uptake bridges to future activity. Uptake is transitive in the logical sense through the *composition of interpretations* (Blumer, 1986; Suthers, 2006b). If uptake u_1 transforms o_1 into o_2, and uptake u_2 transforms o_2 into o_3, then o_1 has been transformed into o_3. More importantly, the act of uptake u_2 is taking up not only o_2, but also taking up the transformation $o_1 \text{—} u_1 \rightarrow o_2$ (the interpretation of o_1 as o_2), so u_2 interprets the prior act of interpreting o_1. This is another way of saying that meaning making is embedded in a successively expanding history.

A participant can take up one's own prior expressions as well as those of others. Therefore, uptake as a fundamental unit of analysis is applicable to the analysis of both intrasubjective and intersubjective processes of learning. An act of uptake is available as form of participation only within a realm of activity in which its transformed object is manifest (e.g., visible, audible, or otherwise available to perception). An individual working through ideas via mental processes and external notations has access to the transformed objects of his or her mental uptake as well as those of acts in the external media, but in the public realm only uptake that manifests via coordinations becomes available for further uptake.

Related concepts. Uptake is similar to several other relational units of interaction in the literature, as it is intended to identify a more general conception that underlies them all. The *thematic connections* of Resnick, Salmon, Zeitz, Wathen, and Holowchak (1993) are examples of uptake, although uptake allows for nonlinguistic forms of expression, and for other kinds of interpretative acts in addition to thematic or argumentative ones. Uptake has the advantage of being neutral with respect to the type of relationships possible (not being limited to a given set of thematic connections). An assertion that uptake is present postulates that a manifestation or trace of prior action has been taken as having significance for further activity, but abstracts away from what aspect of the prior action is brought forward, or what significance is attributed to it. This means that uptake is only a step on the way to identification of theory-specific relationships, for example, thematic connections or other interactional relationships captured by coding schemes (e.g., Berkowitz & Gibbs, 1979; De Wever et al., 2006; Herring, 2001; Rourke et al., 2001; Strijbos, Martens, Prins, & Jochems, 2006). However, unlike coding schemes, uptake meets the criterion of impartiality toward interpretations, so it can provide a common foundation for comparison of different interpretations.

Uptake is related to but is broader than the concept of *transactivity,* which is often defined as reasoning that operates on the reasoning of one's partner, or peers, or of oneself (Azmitia & Montgomery, 1993; Kruger, 1993; Teasley, 1997; Weinberger & Fischer, 2006). The transactivity literature focuses on interactional contexts in which a contribution is explicitly directed toward an identified other, as in, for example, Berkowitz and Gibbs' (1979) coding categories for dyadic discussion. Uptake is broader in that it includes situations where an actor takes up a manifestation of another actor's coordination without the necessity of either person knowing that the other exists, as happens in distributed asynchronous networks of actors in which resources are shared. Taking-up need not be directed at anyone. There are also differences in the analytic practices associated with each concept. Some analysts, such as Berkowitz and Gibbs (1979) and Azmitia and Montgomery (1993) who use their coding scheme, treat transactivity as a property of individual utterances that can be identified by observing the other-directedness of the utterance. Our proposal concerning uptake as an approach to analysis is relational. One cannot assert uptake as a property of an individual act: It is evidenced by contingencies between acts. However, the concepts of transactivity and uptake are compatible, with uptake being inclusive of transactive relationships.

The relationship between uptake and the distinct conversation analytic concept of *preferences* is worth a brief note. At a given moment in a conversation, speakers may elect to continue the conversation in ways that differ in how they are aligned with the immediately prior contribution, some being more aligned or "preferred" (Atkinson & Heritage, 1984; Schegloff & Sacks, 1973). The meaning of the next utterance derives partially from how it meets these expectations. In a conversational setting, uptake either selects some aspect of the prior contribution as being relevant in a certain way, thereby making a commitment (whether more or less preferred) concerning alignment to prior contributions, or denies this relevance by taking up instead some other act as relevant. In either case, a new set of preferences is offered based on the aspect of the prior act selected as being relevant.

Epistemological utility, not ontological claim. Although we have described uptake as something that participants do, uptake is more accurately understood as an etic abstraction used in the analytic practices of identifying interactionally significant relationships between acts. From an emic perspective, participants do not engage in the abstract act of uptake; they engage in specific acts that they affirm (through subsequent acts) as the accomplishment of recognizable activity (Garfinkel, 1967). Thus, from an ontological standpoint (concerning the nature of the actual phenomenon), uptake provides an inadequate account. However, from an epistemological standpoint (concerning the process by which analysts come to know the phenomenon), uptake and its empirical support, contingency, can be useful abstractions. For example, in a large data set, it may be useful to identify the possible loci of interaction before constructing an analytic account of the meaning of that interaction. As shown in Figure 1, the analyst's identification of uptake is a bridge between empirical contingencies and further analysis. Uptake analysis is a proto-analytic framework that must be completed by specific analytic methods motivated by a given research program. The contingency graph, described next, provides another resource for this analysis by offering potential instances of uptake and grounding analysis in empirical events.

Empirical and Representational Foundations: An Abstract Transcript

Although we are ultimately interested in analyzing interaction in terms of sequences of uptake, one cannot jump immediately from raw data to uptake. Human action is deeply embedded in, and sensitive to, the environment and history of interaction in many ways, while only some of these contingent relationships enter into the realm of meaning in which participants are demonstrably oriented toward manifestations of prior activity as having relevance for ongoing participation. An analytic move is required to identify those observable contingencies that evidence uptake, and accountability in scientific practice requires that this analytic move be made explicit. This move is complicated when interaction is distributed across media, as no recording of a single medium contains all of the relevant data. Also, the complexity of potential evidence for uptake and our desire to scale up analysis suggests that computational support is required. Motivated by the need for a transcript representation that exposes interactional structures in diverse forms of mediated interaction, and for a formal structure that is amenable to computation, we developed the *contingency graph*. These empirical and representational foundations for the practices of uptake analysis are described in this section.

Events and coordinations. Uptake analysis begins with selection of a set of observed events. Events in general, rather than strictly coordinations, are included for two reasons: First, data collection and computationally supported analysis may begin before subsequent analysis identifies which events constitute coordinations; and second, actors' coordinations may take up environmentally generated events that must be included to understand those coordinations. Therefore, contingency graphs are defined over sets of events that include but need not be limited to coordinations. Examples of coordinations include utterances, electronic messages, and workspace edits. Later, we will see that coordinations may be specified at larger granularities, for example, a sequence of moves that creates a graphical arrangement of elements. Examples of events that are not coordinations include display updates driven by environmental sensors or by coordinations that took place on other devices. Events are represented in the formal contingency graph by vertices, and are depicted by rectangular nodes in the figures (e.g., e_1 and e_2 in Figure 1 and $e_1 \ldots e_4$ in Figure 2).

Contingencies. If a coordination is to be interpreted as taking up a prior coordination or event, then there must be some observable relationship between the two. Therefore, we ground uptake analysis in empirical evidence by identifying *contingencies* between events. A contingency is an observed relationship between events evidencing how one event may have enabled or been influenced by other events. The concept of contingency recognizes that "there might exist many metaphysical shades between full causality and sheer inexistence" (Latour, 2005, p. 72) between events that underlie the myriad of ways in which human action is situated in its environment and history. This situatedness is not bounded arbitrarily: Relevant contingencies include spatially and temporally local contingencies, but also can include non-local contingencies at successively larger granularities (Cole & Engeström, 1993; Jones et al., 2006; Suthers & Medina, 2010). Contingencies can be found in media-level, temporal, spatial, inscriptional, and semantic relationships between coordinations: These will be discussed in the next section. Ideally, contingencies are based on manifest rather than latent relationships between events (Rourke et al., 2001), and can be formally specified and mechanically recognized.

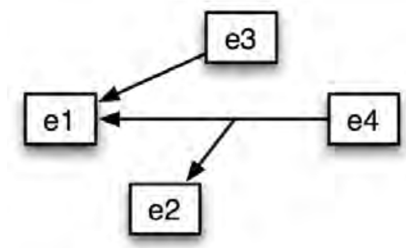


Figure 2. Contingency graph

Contingency graph. The contingency graph is a directed acyclic graph consisting of events and the contingencies between them on which we may layer analytic interpretations. Formally, the contingency graph is a one-to-many directed hypergraph G=(V, E). The set of vertices V is the set of events selected for analysis, and the set of directed hyperedges E records all the prior events on which each event is directly contingent. E is a set of tuples $(e_u, \{e_1, ... e_n\})$, $e_i \in V$, where event e_u is contingent on events e_1 through e_n. For example, the graph depicted in Figure 2 consists of $V = \{e_1, e_2, e_3, e_4\}$ and $E = \{(e_3,\{e_1\}), (e_4,\{e_1,e_2\})\}$.

A contingency graph respects the chronology of events: If the subscripts are time stamps under a partial ordering ">" then in each contingency $(e_u, \{e_1, ... e_n\})$, $u > i$, for $i = 1, ... n$. In a *normalized* contingency graph, none of $\{e_1, ... e_n\}$ are contingent on each other. (Formally, if $(e_u, \{e_1, ... e_n\}) \in E$, then for any two e_x and e_y in $\{e_1, ... e_n\}$, there does not exist a tuple $(e_y,\{... e_x ...\})$ in E.) Normalization keeps the size of tuples to the minimum necessary and prevents redundant paths in the contingency graph, so that it is easer to find all the prior events upon which a given event is directly contingent. In many of our analyses, we partition V into $\{E_0, C_1 \dots C_m\}$ according to which participant 1…m enacted the coordination, with E_0 reserved for events by nonhuman actants. If some of $\{e_1, ... e_n\}$ were by a different participant than e_u (i.e., one of $e_1 ... e_n$ is in a different partition than e_u), then there are intersubjective contingencies, and the potential for collaboration exists.

The contingency graph is an *abstract transcript representation.* By calling it "abstract," we emphasize two things. First, all transcripts are abstractions of the events themselves, but contingency graphs abstract further from media-specific transcript formats to a common format. Second, the contingency graph is a formal object. It should not be confused with *implementations.* One need not construct the entire contingency graph for a given data set; indeed, it may not be possible to do so. The actual implementation may create data structures for whatever portions are sufficient and tractable for purposes at hand, or may merely trace out contingencies as needed. Similarly, the contingency graph is not a type of *visualization*: it is an abstract formal object that can be visualized in different ways. One need not visualize the graph as a node-and-link diagram as in Figure 2: It may be queried and manipulated through other visualizations. The value of a contingency graph lies in making the structure of the data available in a media-independent manner while also indexing to that media.

Contingencies provide evidence that uptake may exist, but do not automatically imply that there is uptake. Uptake is manifest in many ways evidenced in each instance by multiple corroborating contingencies. Once uptake has been identified, it may be represented using an *uptake graph*, as in Suthers (2006a). An uptake graph is similar to a contingency graph, but may collect together multiple contingencies into a single uptake relation.

Constructing Contingency Graphs

This section describes the practical tasks involved in producing a contingency graph, and discusses these tasks in relation to existing analytic practices.

Identifying Events and Coordinations

Any analysis selects events that the analyst believes are relevant to the analytic question. For example, when an analyst transcribes an audio or videotape into Jeffersonian notation, the transcript is necessarily less rich than the original data: The analyst is selecting those events that she believes are relevant for further analysis. The act of "segmentation" common in some methods identifies units of the data representation (segments) that are suitable as meaningful units for the purpose of analysis. Similarly, an analyst may identify points of interest in a media recording or extract events from software log files. Identification of events believed to be relevant to the analytic question is also the first step of constructing a contingency graph. Doing so follows existing analytic practice, but makes this practice explicit by representing events as vertices in the contingency graph. The practice of explicitly identifying the events on which an analysis is based makes clear the specific events that were seen as relevant and helps expose assumptions. This helps multiple analysts collaboratively review their observations and interpretations. The contingency graph should allow the analyst to return to the event as accounted in the data record.

As analysts of collaborative learning, we are particularly interested in participants' acts that coordinate with the public realm. Some coordinations are easy to identify. When analyzing spoken conversation or discussion forums, utterances and messages (respectively) are obvious candidates for coordinations. The creation or editing of an object or inscriptions in a shared workspace is similarly easy to identify as coordination. We use the general term *expressions* to refer to coordinations that produce manifestations potentially available to others.

Perceptions (e.g., seeing or hearing an expression) are another form of coordination between personal and public realms. Some analyses do not attempt explicit identification of perceptions, and may implicitly assume that every contribution is available to others at the time the contribution is produced or displayed. With asynchronous data, this assumption is clearly untenable. The applicability of this assumption to some forms of quasi-synchronous interaction can also be questioned. For example, we cannot assume that a chat message was perceived when it was produced. Active participants may have scrolled back into the chat history, or may be attending to an associated whiteboard. In our own work, maintaining the distinction between expression and perception has forced us to question our assumptions about which coordinations are available to others, and when. The contingency graph can include explicit specification of evidence for perceptions as another form of coordination. Perceptual coordinations are usually difficult to identify, but in some data, observable proxies such as opening a message are available. This is useful information for some analyses, such as tracing information sharing.

We have found it necessary to include events generated by nonhuman actors in our contingency graphs. For example, consider asynchronous computer-mediated interaction. A person engages in an expressive act that results in a change in the digital environment, such as the creation of an object in a workspace or the posting of a message. Later, another person connects to the workspace or discussion and the software system displays the object or message on that person's device. The recipient's perception of the new object or message is contingent upon and cannot occur prior to this automated display. This is an important distinction to make in order to track availability of inscriptions and avoid making unwarranted inferences. Vertices can be included for any event in the environment for which we claim analytic relevance.

Identifying Contingencies

Another task in constructing a contingency graph is to identify and document the contingencies between events. Contingencies map out the sequential unfolding of the interaction. They are defined in terms of participating events (e_u, {e_1, ... e_n}), and evidence for the contingency.

The term *contingency* is introduced to make an important distinction between the identification of *evidence* and the identification of *interpretations* in analytic practice. In many coding methods, the analyst simply asserts relationships between acts, for example, that a contribution is an "elaboration" on or "objection" to another. Measures of inter-rater reliability are used to establish that there is sufficient agreement among the judgments of those researchers participating in the analysis, but validity is not addressed because the basis for judgment is not made explicit and available to other researchers. We advocate for separating evidence from interpretation by first identifying manifest (as opposed to latent; Rourke et al., 2001) features of coordinations and ways in which they are contingent upon the environment and history, before interpreting these features and contingencies as evidence for interactional relationships of interest. This approach facilitates sharing and scrutiny of data and analyses, and provides a representational foundation for scaling up interaction analysis with machine support.

In our own work, we have identified several contingency types, summarized in Table 2 and discussed below along with examples. The most obvious contingencies are *media dependencies*, which are present when an action on a media object required the existence of a previous action that created the object or left it in a prerequisite state. For example, a reply in a threaded discussion depends on the prior creation of the message being replied to, and modifying an element of a shared workspace depends on the most recent act that modified the element.

Media dependencies can include perceptual coordinations. Consider a reply in a threaded discussion. The creation of the reply message is contingent on the author's perception of the message being replied to (and possibly on other perceptions), which, in turn, is contingent on the creation of the message. The importance of this distinction will be exemplified later, in the example associated with Figure 10, where the inclusion of contingencies involving read events gives a dramatically different impression of the coherence of a discussion. However, for many analytic purposes or when evidence for perceptual coordinations is not available, it is sufficient to work with contingencies between expressive acts.

Temporal proximity is important in analysis of spoken dialogue and interaction in other media where contributions are expected to be relevant to ones immediately prior. Contingencies based on temporal proximity need not be limited to adjacent coordinations: They can extend in time based on the

Table 2. Summary of types of contingencies of e_i on e_j.

Media dependency	e_i operates on a media object or state of that object that was created or modified by e_j.
Temporal proximity	e_i took place soon after e_j, where "soon" depends on the attentional properties of the agent and persistency of the medium
Spatial organization	The locality of inscriptions operated on in e_i is in a spatial context created by e_j.
Inscriptional similarity	e_i creates inscriptions with visual attributes similar to those of inscriptions created by e_j.
	e_i creates inscriptions with lexical strings identical to those in inscriptions created by e_j.
Semantic relatedness	The meaning of inscriptions created by e_i overlaps with that of inscriptions created by e_j.

attentional and memory properties of the agents and on the persistence and availability of the media involved. For example, a comment by a conference delegate on the quality of posters at a conference may be contingent upon posters viewed during that poster session; and a message posted in a threaded discussion may be contingent on messages read previously during the login session. We might assume that temporal contingencies weaken with the passage of time, though it is difficult to quantify this degradation in a satisfying manner.

Contingencies based on *spatial organization* may be useful for analysis of interaction in media where spatial placement can be manipulated by participants. For example, contingencies can be asserted when coordinative acts place objects in proximity in a two-dimensional workspace. If two items are placed near each other in a workspace, this may be an expression of relatedness. This example illustrates the more general principle of not confusing the representational vocabulary of a medium with the actions supported by the medium. For example, a medium that supports spatial positioning may be used to create groups even if no explicit grouping tool is provided (Dwyer & Suthers, 2006; Shipman & McCall, 1994). Membership in configurations such as lists may also be asserted as contingencies. Spatial contingencies merely record the fact that the placement of one object near the other depends on the prior placement: Whether we interpret this organization as some kind of grouping or categorization is the concern of further analysis.

Inscriptional similarities are often used by actors to indicate relatedness (Dwyer & Suthers, 2006). For example, inscriptions can have similar visual attributes (e.g., color or type face), shapes can be reused, or lexical strings can be repeated. Contingencies are asserted between coordinations based on inscriptional similarities to record the possibility that the reuse of the inscriptional feature indicates an influence of the prior coordinations $\{c_1, \ldots c_n\}$ on c_u.

Semantic relatedness may be asserted when the semantic content of a coordination overlaps with that of another coordination in a manner that requires recognition of meaning (not merely inscriptional similarity). For example, if one inscription contains the phrase “environmental factors” and another contains the phrase “toxins in the environment,” and these are considered to be related ideas in the domain under discussion, then a semantic contingency might be asserted. However, these are latent rather than manifest relations, so care must be taken to not assert semantic contingencies that assume the uptake for which those contingencies are to serve as evidence.

In general, contingencies are more convincing as evidence for uptake if multiple contingencies are present offering convergent evidence (e.g., temporal proximity *and* lexical overlap between the same two coordinations). Therefore, it can be important to identify several types of contingencies and to interpret contingencies between coordinations collectively.

Documenting Other Aspects of Interaction

A contingency graph is a partial transcription of an interaction. It may be necessary to annotate or augment the contingency graph formalism to contextualize the interaction. For example, the reply structure of a threaded discussion is an important resource for understanding the participants’ view of the medium, and so may be included as annotations on contingency graphs. In asynchronous settings, it can be important to document workspace updates by which participants received new data from their partner. These updates can be represented in the contingency graph as vertices for events in which the technological environment is the actant.

Role of the Contingency Graph in Analysis

The contingency graph was developed to support diverse studies in our laboratory, including multiple methods of analysis applied to a single source of data, as well as to help integrate our thinking about interaction across several sources of data. The contingency graph can be used for analysis in various ways, and methods cannot be described without giving the context in which they were applied. Therefore, detailed explication of how the contingency graph is used in analysis is taken up in the examples starting in the next section. We conclude this section with a few general observations concerning analysis of contingencies and uptake.

Iteration and densification. Production of the contingency graph can be an iterative process of densification in which multiple passes through the data identify additional elements and provide new insights into the interaction (e.g., as in Medina & Suthers, 2009). New events and contingencies can be continually added to the graph. As the recorded data becomes richer, warranted results also scale up. Grounded theory (Glaser & Strauss, 1967) offers tools for iterative analysis, including motivated addition of data through "theoretical sampling." However, the graph can never be considered complete, except with regard to particular representational elements (e.g., it is possible to claim that every discussion posting has been recorded). Therefore, as in any analysis, one must be cautious about asserting that a practice or pattern never occurs.

Directions of analysis. Analyses may take different directions from what is given to what is discovered. A typical distributed cognition analysis starts by identifying a system's function (e.g., collaboratively steering a ship) and explains how that function is carried out by tracing the propagation of information through the system and identifying transformations of that information that take place at points of coordination between the participants and external representations. In settings fundamentally concerned with the creation of new knowledge, it is more appropriate to work bottom-up, starting with the identification of visible acts of coordination and the contingencies between them, and then seeking to recognize what is accomplished through the interaction. A hybrid approach is to start with a recognized learning accomplishment, and then to work backwards in time to reconstruct an account of how this accomplishment came about. An example will be offered in the next section.

In summary, a contingency graph is an abstract transcript that indexes to the original data but indicates the aspects of that data that are chosen for analysis. It is only a starting point for analysis. Collections of contingencies evidence uptake; and sequences of uptakes are interpreted based on the theoretical phenomena of interest, such as argumentation, knowledge construction, or intersubjective meaning making. In practice, the process may iterate between identification of coordinations, contingencies, and uptake; and may be driven by specific analytic goals or may be more exploratory in nature. Because the explication of structure in the data and the analytic interpretation are separated, the contingency graph can serve as a basis for comparison and integration of multiple interpretations. Possible approaches to interpretation are diverse: Some examples are given in the rest of the paper.

Detailed Example of the Contingency Graph Representation

In this section, we provide a simple yet detailed example of how a contingency graph is derived from data, and how that contingency graph can be used for tracing out three fundamental interaction patterns (information sharing, information integration, and round trips). The purpose of this section is to help the reader understand the contingency graph as an abstract data representation, to illustrate how to trace out intersubjective meaning making in the graph representation, and to introduce the visual notations we use to display graphs. Our claim that it is a useful analytic representation will also be addressed with additional examples in the next section. The example in this section and two examples in the next section are based on data derived from dyads interacting in a laboratory setting. Therefore, we begin by briefly explaining the source of the data.

Asynchronous Dyadic Interaction in a Laboratory Setting

The data is derived from an experimental study of asynchronously communicating dyads, conducted to test the claim that conceptual representations support collaborative knowledge construction in online

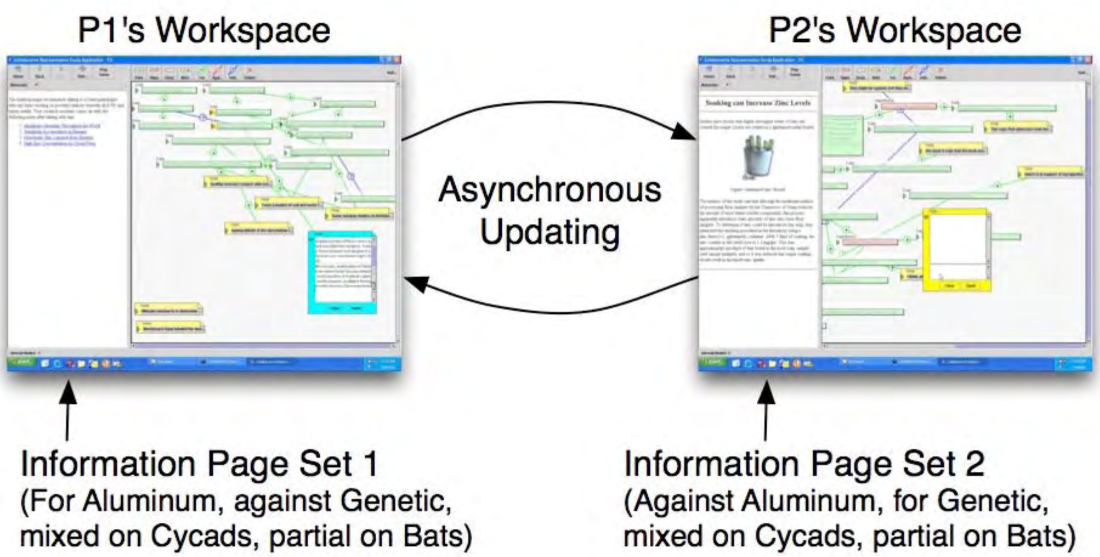


Figure 3. Interacting through graphical workspaces

learning more effectively than threaded discussions (Suthers, 2001; Suthers et al., 2008). Participants interacted via computers using evidence mapping and threaded discussion tools in a shared workspace to identify the cause of a disease on Guam (Figure 3). Three conditions were tested: threaded discussion only; threaded discussion side by side with evidence map; and evidence map with embedded notes (the latter is shown in Figure 3). Information was distributed across participants in a hidden profile (Stasser & Stewart, 1992) such that information sharing was necessary to refute weak hypotheses and construct a more complex hypothesis. The protocol for propagating updates between workspaces was asynchronous. Process data included server logs and video capture of the screens. Outcome data included individual essays that participants wrote at the end of the session, and a multiple-choice test for both recall and integration of information that participants took a week later. Results reported elsewhere (Suthers, Vatrapu, Medina, Joseph, & Dwyer, 2007; Suthers et al., 2008) showed that users of conceptual representations (the two conditions with evidence maps) created more hypotheses earlier in the experimental sessions and elaborated on hypotheses more than users of threaded discussions. Participants using the evidence map with embedded notes were more likely to converge on the same conclusion and scored higher on posttest questions that required integration of information distributed across dyads. One possible explanation for these convergence and integration results is that the higher performing group shared more information, but this explanation was not supported by analysis of essay contents and posttest questions designed to test information sharing. Therefore, we undertook further analyses to explore information sharing during the session.

Motivation for the Analysis

Some of our analyses sought to identify whether and how the construction of the essays was accountable to the prior session, and especially whether interaction between participants influenced the essays. For each session analyzed, we began with the participants' essays and traced contingencies back into the session (constructing the contingency graph as we went) to identify uptake trajectories that may have influenced the essays. Some sessions were chosen for analysis because there was convergence in the content of the essays and we wanted to identify how this convergence was achieved interactionally. Other sessions were chosen to examine divergent conclusions. In both cases, we wanted to relate significant instances of intersubjective uptake or failure thereof to how participants used the media resources. The first example presented below is of the former type, where participants converged in their individual essays.

Elements of a Contingency Graph

In this section, we illustrate how elements of a contingency graph are related to interaction data, drawing on an analysis we conducted for one session. Both participants (referred to as P1 and P2) mentioned "duration of exposure" to environmental factors or toxins in their essays, and the analysis sought to identify how this convergence in the individually written essays was accomplished. We constructed a contingency graph by working backwards from the events in which each participant wrote this explanation to identify the contingencies of these writings on prior events. We constructed the contingency graph in OmniGraffle™ and Microsoft Visio™ based on inspection of software log files (imported into Microsoft Excel™) and inspection of video of participants' screens (recorded in Morae™). The contingency graph we constructed focused only on the interaction relevant to the aforementioned essay writing events, and includes about 180 events and 220 contingencies between them. A visualization of a small portion of this graph is shown in Figure 4. The rounded boxes with text in them summarize the logged events on which the presented portion of the graph is based. These are included solely as expository devices and are not part of the contingency graph, although graph elements should always index back to their data source. Vertices representing P1's coordinations (the logged events) are shown as black rectangles above the timeline, and vertices representing P2's coordinations are shown as white rectangles below the timeline. Each vertex was assigned an identifier as we constructed the graph, vertices for perceptual coordinations being marked with the letter "p." Time flows left to right, but this being an asynchronous setting we cannot assume that a contribution is available as soon as it is created, nor can we assume that the clocks on each client were synchronized (inspection of the figure will reveal that they were not). The vertical lines in each participant's half demarcate when the local client updated that participant's workspace to display new work by the partner. (These events can be represented as vertices in the contingency graph formalism, but for simplicity we show only vertices for human actors.)

Arrows between the boxes visualize contingencies. Dotted arrows represent intrasubjective and solid arrows represent intersubjective contingencies. For example, contingency (20p, {20}), a media dependency, is present because P1's coordination that took place at 1:50:23, represented by vertex 20p, accessed the media object created by P2 in the coordination that took place at 1:41:40, represented by vertex 20. Although the preceding sentence is technically accurate, it is also tedious. For brevity, we will use the numeric identifier as shorthand to refer to the coordination, any object or inscription that may have resulted from the coordination, or the vertex that represents that coordination. For example, we can state simply that 20p accessed 20's media object, so a media dependency is present. However, we will make the distinctions more explicit when necessary for the point at hand.

This graph illustrates how contingencies can be evidenced by the editing of media objects or by lexical similarity, and can be further evidenced by temporal and spatial proximity. For example, at 1:52:06, P1 added a comment (10) to the same note object that she had just read at 1:50:23 (20p). (A note object can contain a sequence of comments from both participants.) Because the coordination 10 could not have taken place unless this media object existed, we have a media dependency of 10 on 20p. The same example illustrates lexical and temporal contingencies. Coordination 10 uses the phrase "environmental factors," which is present in the note accessed at 20p, providing an inscriptional contingency of 10 on 20p. (Coordination 10 is also contingent on 13 by lexical overlap of "duration of exposure.") Finally, 10 takes place less than two minutes after 20p, providing circumstantial evidence by

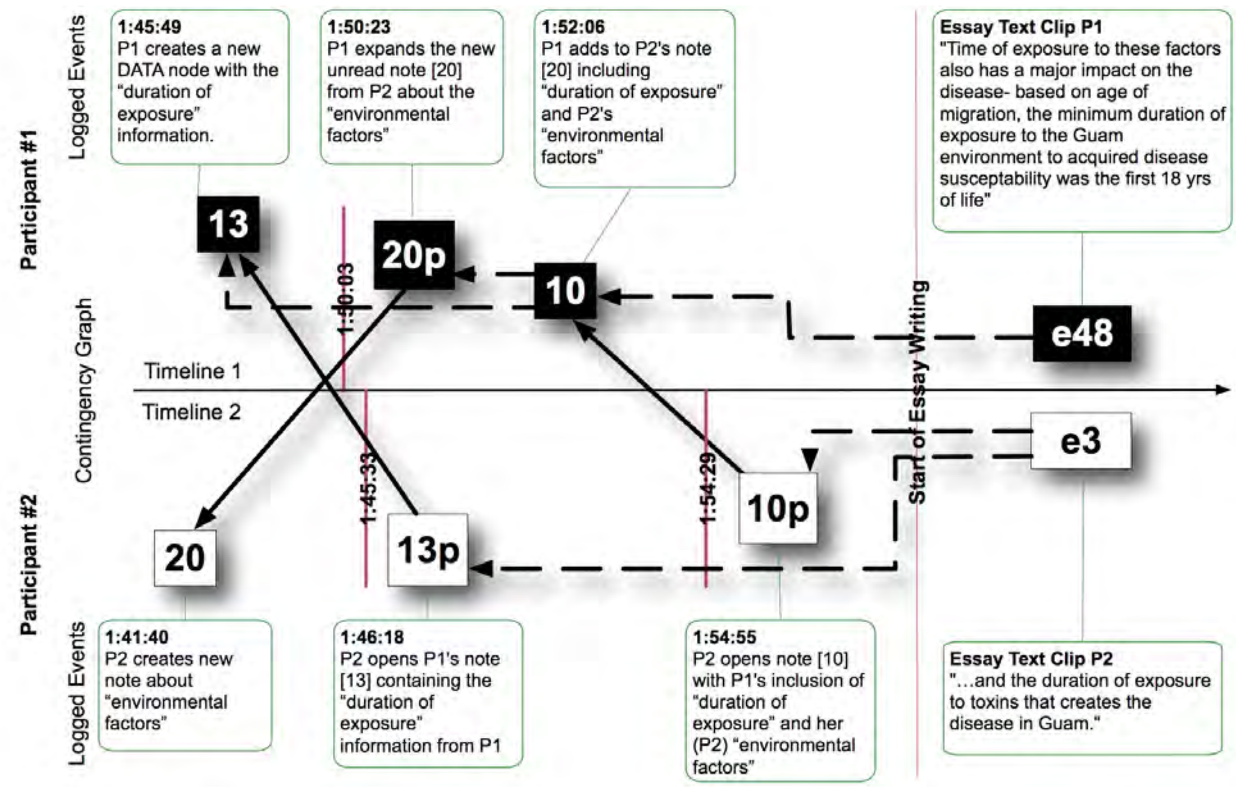


Figure 4. Fragment of a contingency graph and the events from which it was derived

temporal proximity that 10 is contingent on 20p.[1] Therefore, the arrow from 10 to 20p in Figure 4 visualizes a composite of three contingencies that we take as evidence for uptake.

Interpretation of the Contingency Graph

Next we walk through the graph of Figure 4 to trace out the interaction it represents and illustrate its analytic use. Because Figure 4 shows only those composite contingencies we have selected as evidence for uptake, it is also an uptake graph. We show how the uptake structure can be interpreted in terms of three phenomena: information sharing, integration of information from multiple sources, and intersubjective round trips.

Sharing information. At 1:41:40, P2 creates a note summarizing environmental factors as disease causes (20). This note is not yet visible to P1. Around then in clock time but asynchronously from the participants' perspectives, P1 creates a data object (13) concerning the minimum duration of exposure to the Guam environment needed to acquire the disease. Subsequently, a workspace refresh (1:50:03) makes note 20 available to P1. P1 opens this note shortly after (20p). The contingency (20p, {20}) could be interpreted as an information-sharing event, as P2 has expressed some information in inscriptions and P1 has accessed these inscriptions. We emphasize that this is an analytic interpretation: There is no requirement that the contingency graph be interpreted in terms of flow of information or shared mental states.

[1] The mapping of temporal proximity to evidential strength is relative to the medium and activity. Here, a person is deliberating over various materials while her partner works asynchronously. A few minutes deliberation is plausible.

Integrating information. Later, P1 adds a comment to the note object (10) that is contingent on 13 and 20p, as discussed in the previous section. We interpret these combined contingencies (10, {13, 20p}) as evidence for uptake in which 10 integrated two lines of evidence about this disease from 13 ("duration of exposure") and 20p ("environmental factors"). Taking the transitive closure of contingencies that pass through perceptual coordinations, the contingencies on expressive events are (10, {13, 20}). Therefore 10 integrates information that originated from each participant P1 (13) and P2 (20) in the hidden profile design.

A round trip. Let us now examine how P1's integration (10) became available to P2. Sometime after 13 was expressed, a refresh (1:45:33)[2] made the corresponding object available to P2, who opened it shortly after (13p). Subsequently (after P2 does other work not shown), another refresh (1:54:29) makes 10 available to P2, soon opened (10p). Because P2 has considered both 13p ("duration of exposure") and P1's indication that duration of exposure is relevant to environmental factors (10p), we view P2's inclusion of these concepts as "the duration of exposure to toxins" in her essay (e3) to be an uptake of both of these conceptions. The *round trip* from 20 through 20p, 10 and back to 10p, namely the path ((20p, {20}), (10, {13, 20p}), (10p, {10})}), represents intersubjective meaning making on the smallest possible scale beyond one-way information sharing (Suthers, Medina, Vatrapu, & Dwyer, 2007). In this case, information provided by P2 (20) is combined with information available only to P1 (13) and reflected back to P2. We cannot rule out that e3 is uptake of only 20 and 13p and, hence, based on a one-way transfer of information, but nor can we rule out that P1's endorsement of the importance of the idea in 10, taken up in 10p, also influenced P2's inclusion of this idea in the essay. It is plausible that both were a factor.

Necessity of Tracking Availability and Access Events

Awareness of representational elements is not symmetrical in asynchronous media. At one point in the session just described, the objects created by coordinations 13 and 20 both existed, but neither was available to the other participant. A contingency graph can record when the media manipulations of other participants become available to a given participant, but analysis cannot simply rely on the appearance of a media object in a workspace. Some analyses will require evidence that a contribution was actually accessed, which is why we need vertices representing perceptual coordinations such as 20p. Notations developed for face-to-face and synchronous communication often assume a single context and immediate availability of contributions. These are reasonable assumptions for those media but significantly limit those notations' applicability to asynchronous media.

Analytic Use of the Contingency Graph

In this section, we provide examples of several analyses we conducted with the aid of the contingency graph formalism, to provide evidence for our assertion that the contingency graph can productively support multiple types of analyses of distributed interaction. Our evidence is that the contingency graph has served in this way in our own laboratory, where we have undertaken both discovery-oriented analysis (ideographic research) and quantitative hypothesis testing (nomothetic research) from the same source of data, the previously described dyads interacting in a laboratory setting. We also conclude with an application of the contingency graph to a different source of data, server logs of asynchronous threaded discussions in an online course, as an illustration of generality across media.

[2] It may seem impossible for an object created at 1:45:49 to become available at 1:45:33. We remind the reader that the computer clocks were not synchronized. The analogy of a time zone may be useful. In real time, 1:45:33 in P2's "time zone" is after 1:45:49 in P1's "time zone." It would have been easy to hide this from readers by changing the time stamps in the figure. However, we decided to leave the discrepancy in to emphasize the point that even if the clocks were synchronized it would be misleading to compare times across the upper and lower half of the figure due to the asynchronous updating, and more importantly, that *the contingency graph can handle partially specified orderings of events from distinct timelines.*

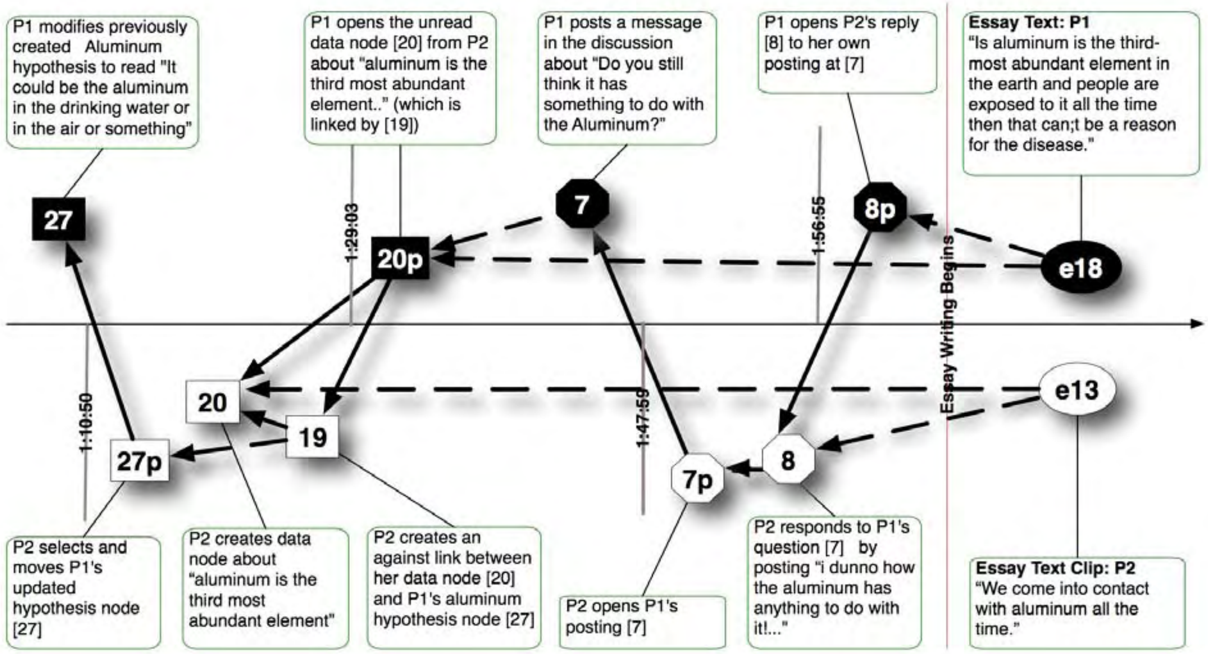


Figure 5. Partial contingency graph of a dyad collaborating with multiple media. Rectangles, octagons, and ellipses represent coordinations with an evidence map, a threaded discussion, and a word processing tool, respectively.

Discovery of an Interactional Pattern

Figure 5 presents a contingency graph derived from a different dyad in the study described previously. This dyad was using a combination of evidence maps and threaded discussions. The analysis was done to understand how these two participants used the available media resources to converge on the conclusion that aluminum in the environment is probably not the cause of the disease under consideration. We were also considering whether convergence is achieved by information sharing alone or whether interactional round trips are required (Suthers, Medina et al., 2007). Construction of the contingency graph allowed us to discover an interesting interactional pattern that goes beyond simple round trips. The information that “aluminum is the third most abundant element” and that this contradicts aluminum as a causal agent were successfully shared via coordinations 27, 27p, 20, 19 and 20p (all of which took place in the evidence map). Specifically, the contingency (27p, {27}) is evidence that P2 is aware of P1’s hypothesis that aluminum is the cause; and the composite contingency (20p, {20, 19}) is evidence that P1 is aware that P2 has expressed the idea that the abundance of aluminum (20) is evidence against this hypothesis (19). From an information-sharing perspective, these two contingencies are sufficient to explain the fact that both the participants mentioned the abundance of aluminum as evidence against aluminum as a disease factor. From an intersubjective perspective, the inclusion of the contingency (19, {27p, 20}) makes this sequence a round trip in which P1’s expression (27) has been taken up (27p), transformed (20, 19), and reflected back to P1 (20p).

The contingency graph exposed a second round trip over 20 minutes later in the session (7, 7p, 8, 8p). This round trip made explicit and confirmed the interpretation implied by the first round trip. By exposing this dual round trip structure, the uptake analysis enabled us to hypothesize an interactional pattern in which information is first shared in one round trip, and then agreement on joint interpretation of this information is accomplished in a second round trip. We call these *W patterns* after their visual appearance in diagrams like Figure 5. The analysis also helped us discover that participants accomplished

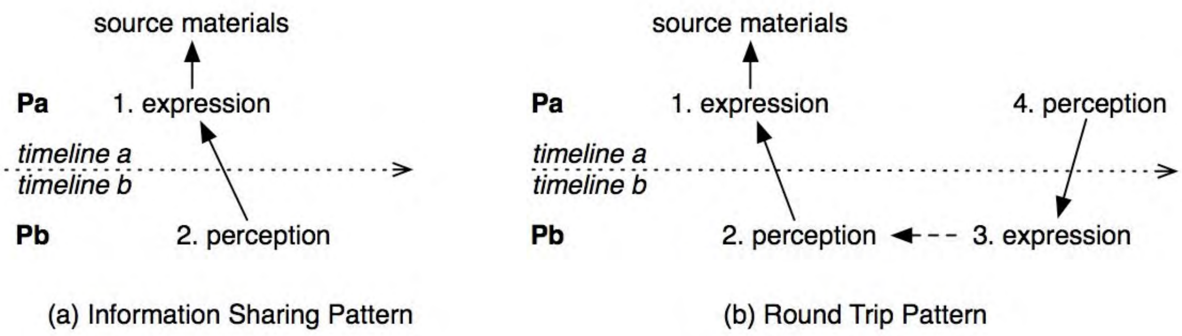


Figure 6. Information Sharing and Round-Trip Patterns

the confirmation round trip in a different interactional medium, the threaded discussion (the coordinations represented by octagons in the figure). The first round trip is reasoning about evidence in the domain, easily expressible in the evidence map notation. The second round trip is reflecting on the status of the domain evidence and how it should be interpreted. This reflection is not as easily expressed in the evidence map, and indeed is a second-order act of stepping outside of that map and interpreting it, so the use of natural language in the threaded discussion seems appropriate. Similar distribution of domain and second-order conversation across evidence maps and synchronous chat has been observed in another study (Suthers, 2006a).

Quantitative Queries for Hypothesis Testing

This example illustrates how contingency graphs can be used to support quantitative hypothesis testing. A study discussed previously found that dyads using evidence maps with embedded notes came to agreement on the disease hypothesis far more than dyads using other software configurations, even though the evidence map users discussed more hypotheses (Suthers et al., 2008). This group also had higher scores on posttest questions requiring integration of information. Given the central role of information sharing in theorizing about collaboration (e.g., Bromme, Hesse, & Spada, 2005; Clark & Brennan, 1991; Haythornthwaite, 1999; Pfister, 2005), one might expect that this group shared more information. We compared the use of shared information in essays, and also compared performance on posttest questions that tested for shared information, but neither analysis supported the assertion that there were differences in information sharing. These being “outcomes” data, we decided to see whether there was evidence for differential information sharing in the sessions themselves. We found all patterns of contingencies in which information uniquely given to one person was expressed in the shared medium and then accessed by the other person (Figure 6a). Our results showed that, measured this way, information sharing in the session was uncorrelated with the convergence results (see also Fischer & Mandl, 2005). Given the apparent importance of round trips observed in the previous analysis, we decided to similarly trace out round trips in the experimental sessions. We found all patterns of contingencies that began with the pattern of the previous analysis, but was further extended in that the recipient then re-expressed the information (possibly transformed or elaborated) in a media object that was then accessed by the originating participant (Figure 6b). Results showed a possible difference (p=0.065) between the experimental groups on round trips (Suthers, Medina et al., 2007). However, a later analysis with post hoc groups formed on presence or absence of convergence did not support either information sharing or round trips as explanations, which presents a problem for the dominant information sharing theory. The negative result on round trips may be due to our failure to track round trips based on hypotheses: see Suthers, Medina et al. (2007) for an explanation.

The point of this discussion is that contingency graphs can also support quantitative hypothesis testing. In particular, basing quantitative analyses on theoretically interesting patterns of contingencies as the fundamental units to be counted can make quantitative studies more relevant to CSCL than studies based on attributes of isolated events or outcome measures alone. A secondary point is that it is not necessary to construct a full contingency graph in advance: In this study, the patterns of Figure 6 were traced out and counted algorithmically in coded log files without constructing an explicit graph representation.

Uncovering Representational Practices through Multi-level Analysis

The next example analysis illustrates four related points. First, automated generation of contingency graphs is possible and can be useful. Second, analysis often uses the contingency graph in conjunction with the source data, and, indeed, part of the value of the graph is to select relevant portions of the source data for further analysis. Third, one can aggregate coordinations and contingencies to discover patterns at a coarser granularity. Fourth, analysis of a contingency graph can lead to insights into nonverbal behavior.

One session from the "evidence map plus threaded discussion" condition was chosen for analysis because participants appeared to converge on the role of cycad seeds in the disease, but not on the role of drinking water. This analysis sought to determine why this might be the case.

Contingency graph construction. Because manual construction of the previous contingency graphs was tedious, we used computational support. In this analysis, the contingency graph was generated through mixed human-computer interaction. We first generated a contingency graph based on media dependencies, by linking sequential chains of events that referenced the same media object (see Medina & Suthers, 2008; 2009 for details). We wrote a collection of scripts packaged into a small application—the *Uptake Graph Utility*—that controls interaction between a MySQL database and Omnigraffle™ (a commercial application for diagramming and graphing) to visualize the contingency graph. See Figure 7 for a portion of the initial visualization of the data under discussion. The Uptake Graph Utility enables one to selectively filter elements of the graph from view, generate subgraphs, and isolate structural or temporal properties of the data. For example, in this analysis, we visualized the subgraph manipulating media objects that contained the strings "drinking water" or "aluminum."

Revealing a nonverbal interaction pattern. A striking feature of the contingency graph was that one participant appeared to be primarily contributing information by creating graph objects, while the other participated primarily by manipulating graph objects, particularly by moving them around. Figure 8 shows this pattern in an annotated portion of the contingency graph. P2 could be moving nodes around in order to see them, or to get them out of the way: Dragging and dropping of graphical objects for these reasons is frequent. However, in this case, the periodic pattern and density of P2's series of movements suggested more deliberate activity. This led us to examine the video record from P2's workstation. We found that P2 was performing a series of graph space reconfigurations to organize information previously shared during the session. After P1 contributed new information, P2 moved nodes to create spatially distinct groups, each of which contained conceptually related items. In addition to this spatial organization, P2 created nodes containing brief categorical labels such as "CYCAD INFO" and linked these nodes to group members to further clarify their inclusion in the group.

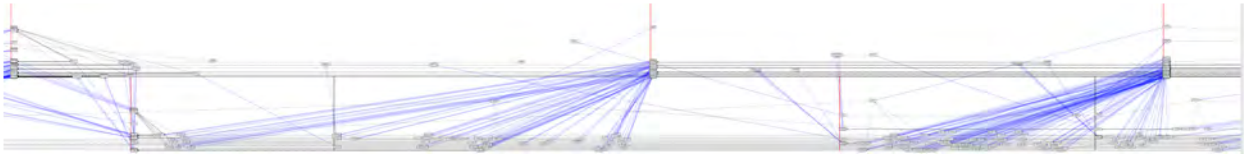


Figure 7. A 20-minute portion of an automatically constructed contingency graph

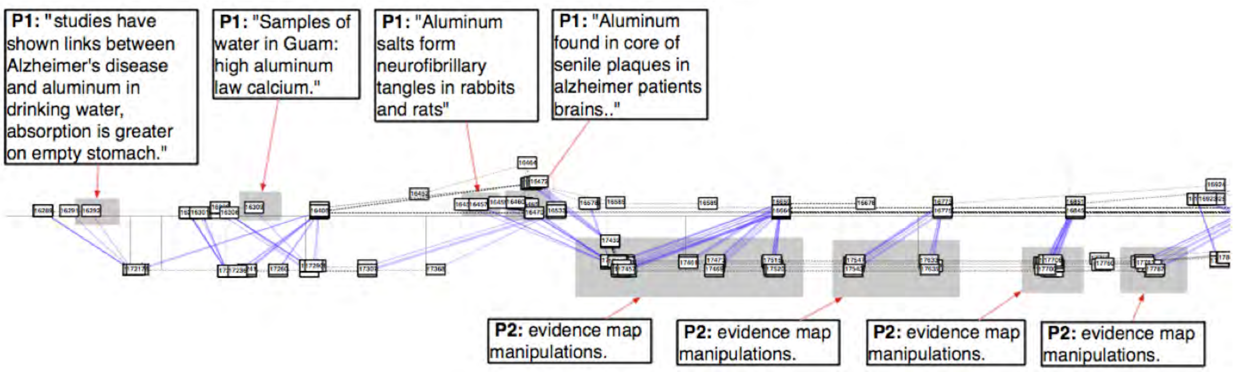


Figure 8. Information sharing by P1 followed by systematic graph manipulations by P2

Figure 9. High level view of uptake over the entire session

Alternation between inspection of the contingency graph and viewing relevant video from both workstations revealed that P1 took up these practices from P2, as detailed in Medina and Suthers (2008, 2009). This led us to identify uptake of information and of representational practices at a coarser granularity, as shown in Figure 9. Beginning at the left, P1 shared information containing a reference to aluminum in water as a contaminant in the first two episodes (E1 & E3). The third information-sharing event by P1 contains two references that correlate aluminum and neurological symptoms of the disease (E6). P2's uptake of this information is seen as episodes of graph space manipulations (E2, E4, E5 & E7-10). Intersubjective uptake within this sequence of activity is initiated in P2's visual transformation of the shared information, and is followed by a series of intrasubjective uptakes as P2 adjusts the representations. As shown in the far right of the diagram, intersubjective interaction resumes when P1 takes up P2's graphical organization in E11, and in the concluding work episode.

Analytic roles of the contingency graph. In this analysis, the contingency graph exposed patterns of interaction and provided direct pointers (via time stamps) to relevant locations in the video record, enabling us to conduct coordinated analysis of the two separate video streams that identified the emergence of a shared representational practice. The contingency graph supported flexible transitions between identification of macro uptake patterns and microanalysis of a series of graphical manipulations during this analysis. Understanding the development of representational practices requires macro and micro understandings (Suthers & Medina, 2010), and the contingency graph mediates between the two. As Lemke states,

> "… we always need to look at at least one organizational level below the level we are most interested in (to understand the affordances of its constituents) and also one level above (to understand the enabling environmental stabilities)." (2001, p. 18)

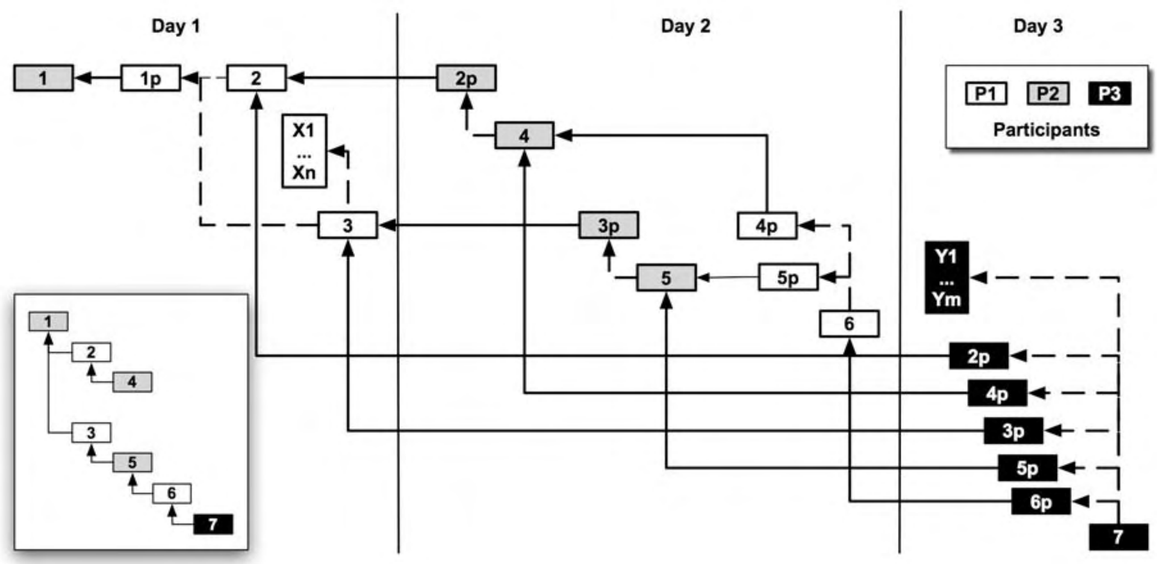
We examined the video record to see how P1 used the affordances of the graph representation to organize information, and we examined uptake at a coarser level over time to see how the persistence of inscriptions in this environment enabled P2 to notice and pick up these practices.

Asynchronous Online Discussion

In order to explore how the contingency graph framework can be adopted to conventional online learning settings, we analyzed server logs of asynchronous threaded discussions in an online graduate course on collaborative technologies. The software (discourse.ics.hawaii.edu, developed in our laboratory) records message-opening events as well as message postings, but there is no other record of participants' manipulations of the screen. Figure 10 diagrams a fragment of the contingency graph we constructed in one analysis. After reading a paper on socio-constructivist, sociocultural, and shared cognition theories of collaborative learning (Dillenbourg, Baker, Blayne, & O'Malley, 1996), a student facilitator suggested that students write "grant proposals" to evaluate learning in the course itself, and discuss how their choice of theory would affect how they approach the evaluation. The episode we analyzed took place over several days, demarcated in Figure 10 by vertical lines for midnight of each day. The reply structure of the threaded discussion is shown in the inset, lower left of Figure 10. The episode of Figure 10 was chosen because it illustrates conceptual integration across two subthreads, and, hence, the analytic value of contingencies that are independent of media structure.

Stepping through our interpretation of the graph, in 1 the instructor (P2) has posted a comment concerning a prior contribution that used the phrase "socio-cultural" but seemed to express a socio-cognitive approach. Unfortunately, "socio-cognitive" had not been discussed in the paper, and the student (P1) reading this message (1p) is confused by the different name. She raises questions about the distinction in two separate replies, 2 and 3. Between 2 and 3, she has read a sequence of messages ($X_1 \ldots X_n$): P1 appeared to be searching for more information on the topic. The next day, P2 returns, sees 2 (2p), replies with an explanation of "socio-cultural" in 4, and then starts down the other subthread. Seeing 3 (3p) the source of the confusion becomes apparent and P2 replies with a terminological clarification (5). Later that day, P1 reads both threads (4p, 5p) but replies only to the second with a "thank you" (6). On the third day, P3 reads messages in another discussion ($Y_1 \ldots Y_m$), enters this discussion and reads both threads (2p, 4p, 3p, 5p, 6p), and then replies to the last "thank you" message with a comment (7) about the confusion that related back to the other discussion: an integrative move that was consistent with her assigned role as student facilitator for this assignment.

Participants' reading and posting strategies as well as the default display state and no-edit policy of the medium affect whether conversations are split up or reintegrated. By posting two separate replies (rather than editing her first reply—not allowed—or responding to that reply), P1 opens up the possibility of a divergent discussion. By following a strategy of reading and replying to each message one at a time, P2 continues the split that P1 has started. The discussion tool also allows one to scroll through a single display of all messages that one has opened in a discussion forum. By following a strategy of reading all messages before replying, P3 brings these separate subthreads together. However, the reply structure imposed by the discussion tool does not allow this convergence to be expressed in the medium: P3 must reply to one of the messages, so she replies to the last one she read.



1	P2	9/23 3:39	"… In your first post, your needs assessment seems to be talking about socio-cognitive rather than socio-cultural…"
2	P1	9/23 11:15	"What is the "socio-cognitive" approach? I'd like to read more about this approach since I am not familiar with it. I was really interested in the socio-cultural approach because it seems to imply that intellectual development is directly related to socialization. "
3	P1	9/23 11:31	"I didn't see any description of the "socio-cognitive" approach in the assigned readings. I was not familiar with this approach… "
4	P2	9/24 2:33	"...what is unique about socio-cultural (or CHAT - cultural historical activity theory) is the emphasis on cultural and social context. But you are right, it does give an account of individual cognitive change as a function of social interaction... "
5	P2	9/24 2:34	"...Sorry, I meant socio-constructivist (though I have used socio-cognitive to include the former). ... "
6	P1	9/24 3:35	"Thank you - that clears it up for me! :) "
7	P3	9/25 10:14	"I noticed that several of our grant proposals mixed up socio-cognitive for the socio-constructivist. I was thrown a little at first. Anyone know where the confusion stems from? "

Figure 10. Fragment of contingency graph for an online discussion. Inset lower left shows threading structure.

Many analyses of online discussion consider only threading structure, which provides an oversimplified record of interaction. If the analysis examined threading structure alone (inset of Figure 10), it would not be clear why P1 posted two separate questions (2 and 3), and P3's message (7) would seem odd as a reply to the "thank you," as it is referring to "several of our grant proposals." But the contingency graph captures aspects of the coherence of the mediated interaction that are not apparent in the threaded reply structure. The contingency graph reveals that P1's second posting was motivated by an attempt ($X_1…X_n$) to find the new phrase ("socio-cognitive"), and that P3 had read through a discussion of grant proposals ($Y_1…Y_m$) about an hour before posting 2.[3] Although some of this coherence can be recovered through analysis of quoting practices (Barcellini, Détienne, Burkhardt, & Sack, 2005), our analysis goes further to include (for example) lexical and temporal evidence for coherence, evidence that

[3] In disCourse, a list of who has read each message at what time is available to participants on demand in a separate display, but this analysis suggests that other awareness visualizations may be useful, such as summaries of activity prior to a posting.

can also be partially automated. This ability to identify trajectories of participation that are independent of yet influenced by media structures is an important strength of the method.

Summary and Discussion

The relationship between interaction and learning is a central concern of the learning sciences. Computer-supported collaborative learning itself has been defined as "a field centrally concerned with meaning and practices of meaning making in the context of joint activity and the ways in which these practices are mediated through designed artifacts" (Koschmann, 2002). Our research focuses this agenda on how technology affordances (designed or otherwise) influence and are appropriated by participants' intersubjective meaning making (Suthers, 2006b). We take the concept of "interaction" broadly, to include not only co-present interaction that is tightly coordinated to maintain a joint conception of a problem (Teasley & Roschelle, 1993), but also distributed asynchronous interaction in online communities (Barab et al., 2004; Renninger & Shumar, 2002), and even indirect ways in which individuals benefit from the presence of others in "networked learning" (Jones et al., 2006). In a world in which connectivity is ubiquitous and the distinction between "online" and "offline" is no longer defensible, these forms of interaction will become increasingly mixed in any learner's experience, and the boundary between them will become less clear. Therefore, researchers studying learning through interaction are well advised to work with a fundamental conception of interaction that underlies its various forms.

Our own research has included and continues to include instances of all of these forms of interaction, including dyads interacting face-to-face, synchronously via computer and paper media, and asynchronously; and larger numbers of participants interacting directly and indirectly in online sociotechnical systems. The framework reported in this paper is the result of our effort to provide theoretical coherence to our research while also addressing practical problems in the study of distributed interaction. These two objectives are related. We found that some theoretical accounts were expressed in terms derived from the properties of media they studied, while we wanted to use a single conceptual framework. The practical problems began when we tried to apply methods of face-to-face interaction analysis to distributed interaction. The interaction was distributed across actors, media, and time, and included asynchronous as well as synchronous interaction, making traditional transcript representations and analytic concepts unsuitable. Also, we needed to integrate data recorded in diverse formats. Therefore, we realized it would be valuable to collect the various records of interaction into a single analytic artifact that does not assume a particular interactional context and that can be inspected for evidence of distributed interaction and phenomena at multiple granularities. Due to eclectic work in our laboratory, we needed to support multiple methods of analysis. In particular, we wanted to apply sequential analysis of interaction to expose the methods by which participants engage in intersubjective meaning making, apply computational support to scale sequential analysis up to larger data sets, and also support statistical testing of hypotheses concerning patterns of interaction. A further objective we set for scientific accountability was to separate the empirical evidence and the claims being made while also identifying the relationships between the two.

Over time, our efforts to address these problems and objectives resulted in the framework for analysis reported in this paper. The empirical foundation of the framework is the identification of *events* and *contingencies* between them. The representational foundation of the framework is an abstract transcript, the *contingency graph*, which represents events as vertices and contingencies as edges. The conceptual foundation of the framework in terms of which interaction is identified is *uptake* between *coordinations*. We have applied this framework to data derived from synchronous and asynchronous interaction of dyads and small groups, as exemplified in this paper and other publications, and have found it helpful in unifying diverse research in our own laboratory.

While a commitment to contingencies between events is inseparable from this framework, the contingency graph may be adopted independently of the concepts of coordinations and uptake. The contingency graph provides a single representation of data that applies to diverse contexts and forms of interaction, supports computational tools for scaling up sequential analysis, enables quantitative methods to operate on interactional patterns, and separates empirical grounds from interpretation. The contingency graph is media-agnostic. It records the multiple coordinations that took place in an interaction and maps out their interdependencies. However, it is not media ignorant; it can bring in medium-specific information and index to media recordings, so the relationship between meaning making and the media can be examined.

We find the concept of uptake useful in interpreting contingency graphs. An uptake analysis makes commitments to intentional agency by identifying coordinations, and then uses corroborating contingencies to identify ways in which coordinations demonstrably take manifestations of prior participation as relevant to ongoing participation. Abstracting a contingency graph to an uptake graph enables one to trace out individual trajectories of participation, to examine how these trajectories affect each other; and to step back and analyze the composite web of interpretations that constitutes "distributed cognition" (Hutchins, 1995) or "group cognition" (Stahl, 2006). Furthermore, we find the concept of uptake to be useful for questioning assumptions concerning what constitutes interaction and thinking about interaction in the diverse forms it takes.

Related Work

The uptake analysis framework has strong affinities with the Constructing Networks of Activity Relevant Episodes (CN-ARE) approach (Barab, Hay, & Yamagata-Lynch, 2001), although we offer a framework rather than one method, and there are differences in granularity of analysis. As the name implies, Activity Relevant Episodes (ARE) are episodes (rather than events) that have been analytically identified as being relevant to activity in the activity theoretic sense. Barab et al.'s AREs are larger units than events, and are identified further into the analytic process than events. Contingency graphs could be constructed on AREs, but they also can be constructed on automatically selected events prior to identification of the relevance of events (or episodes) to an activity. In the uptake analysis framework, the contingency graphs are the input to the analytic process: No prior coding other than identification of latent events and contingencies is needed. In CN-ARE, the AREs are the product of an analytic process of identifying and coding segments. AREs are defined in terms of "core categories" such as "issue at hand," "instigators," and "practices," categories that could be the output of uptake analysis at a finer granularity.

The "links" of CN-ARE and our "contingencies" are very similar if not identical ideas. Links are

> "… anything that ties one node ... to any other node. Thus, conceptually, all our codes can serve as links between nodes. Time links nodes historically, practices link nodes of similar practices together, resources link nodes of specific resources used together, and initiator and participant codes link people." (Barab et al., 2001, p. 78).

In our framework, many of these relationships between events can serve as contingencies, although our analyses are applied at a finer granularity to identify practices as displayed by sequences of coordinations rather than to assume them as properties of single episodes, and we prefer to apply analytic interpretations to relationships between acts or patterns of uptake rather than to single acts or episodes treated as "nodes."

In CN-ARE, episodes are organized along an ordinal timeline. In the contingency graph, contingencies are the fundamental organizer of events rather than time. Timelines may also be included, but we do not assume a single timeline. The CN-ARE practice of following "tracers" is similar to our practices of tracing pathways through contingencies. New work underway at this writing focuses on developing methods for "tracing out the movement, confluences, and transformations of persons, artifacts and ideas in sociotechnical systems" via the contingency graph and derivative representations (Suthers & Rosen, 2009).

In general, we are very sympathetic to CN-ARE, and see potential for productive synthesis when activity-relevant episodes are the right granularity of analysis. Contingency graphs may be applied directly at this granularity or may be used to discover episodes in subgraphs of a contingency graph that are then chunked into AREs for further analysis.

The contingency graph is an abstract data representation, not a modeling tool, but brief comparison to related representations for modeling highlights some important points. State-based representations (e.g., Jeong, 2005; Olson et al., 1994) are not appropriate for distributed interaction because there is no single event at a given time nor a single unit of time common to all actors to which state attributes can be assigned. The confluences of events in distributed systems are too complex to represent as a state. Furthermore, state representations are ahistorical in that they encapsulate all history in the state: The sequential organization of prior events is not accessible from a state, and the sequential development of learning processes is unavailable. Petri net representations summarized by Reimann (2009) and detailed by van der Aalst and Weijters (2005) solve some of these problems. They have superficial similarities to contingency graphs (capturing the sequential organization of events in a partial ordering), but, being process-model representations rather than data representations, they include devices such as conjunctive and disjunctive branching that are not relevant to a record of an actual network of events. Furthermore, significant analytic work has to be done before building these models: The algorithm of van der Aalst and Weijters (2005) requires that instances of the process to be modeled have been identified, that each event has been associated with a single instance of the process, and that each event has been categorized with a code that is unique within its assigned process.

Similarly, the uptake-analysis framework is not a software tool, but brief comparison to software tools for analysis help highlight some affinities and differences with other approaches. Some analytic tools are embedded within particular software environments, enabling replay of recorded sessions (e.g., VMT; Stahl, 2009) and display of derived analytic representations (e.g., Larusson & Alterman, 2007; Teplovs, 2008). In contrast, the uptake-analysis framework has supported both empirical and theoretical integration of investigations in multiple software environments. Several useful analytic tools have been developed that integrate multiple sources of data by aligning them to a single timeline by which they are synchronized during analysis or replay. These include the Collaborative Analysis Tool (Avouris, Fiotakis, Kahrimanis, Margaritis, & Komis, 2007), Digital Replay System (Brundell et al., 2008) and Tatiana (Dyke & Lund, 2009). These efforts are to be commended for developing analytic software and making it available to others, a step we have not yet taken. Generally these tools are developed to support reconstruction of synchronous interaction at a scale experienced by a small set of participants. Partial synchronization via contingencies (or temporal constraints however expressed) between data streams could make future versions of these tools applicable to asynchronous distributed interaction as well. However, scaling up to phenomena arising from distributed interaction between larger numbers of individuals will require stepping outside of the replay paradigm.

Finally, the uptake analysis framework is not a visualization tool. Contingency graphs have been visualized in this paper as node-link diagrams for exposition, but this visualization is not identical to the formal graph-theoretic representation, and other visualizations are possible. For example, it may be useful to visualize contingency graphs using episodic timelines, such as in CORDFU (Luckin, 2003) and CORDTRA (Hmelo-Silver, 2003). Events can be defined using time durations rather than time points, or a recurring sequence of similar events at time points can be aggregated and visualized as a continuous episode (but see Reimann's, 2009, caution concerning treating event-based phenomena as continuous). The potential visualizations are limited only by the underlying ontology.

Limitations

A limitation of the framework is that, in focusing on observed interaction in an event-based ontology, it does not explicitly acknowledge the cultural or historical situatedness of the participants, or address identity and community, except where these constructs might be recorded in terms of prior events. It may be possible to represent influences exogenous to the interaction with contingencies to pseudo-events that exist prior to the interaction.

In interpreting our graphs, we have encountered several issues related to the intrinsic incompleteness of a contingency graph as a data representation. One must be careful not to make inferences based on the absence of events and contingencies in the graph: Any graph is partial and can be extended indefinitely due to the continuous nature of human action. There are risks in conducting an analysis entirely by using the contingency graph. In addition to being a structure of interest in its own right, the graph should be used as an index to the original data. Visualization software can facilitate this by overlaying or simultaneously displaying the graph with the source media (e.g., with tools such as Brundell et al., 2008; Dyke & Lund, 2009).

We have also found that it is important not to fix analysis at one level (Lemke, 2001), and, in particular, that meaningful units may occur at granularities above the granularity at which events are originally identified. Our work has suggested two constructions: (1) interactionally defined representational elements that do not correspond to any explicit representational notation (e.g., defining groups by spatial co-location), and (2) composite coordinations in which two or more media events seem to share a conception (e.g., a sequence of moves that forms a representational configuration). A pressing task is to extend the contingency graph formalism to better incorporate composite events and ambiguities and degrees of association in contingencies. A complete explication of these two items is necessary to extend the potential algorithmic support provided by the contingency graph structure.

Another postulated limitation is actually a strength of the framework. Colleagues have remarked that the number of potential contingencies for any given act is huge, and so the contingency graphs can become quite complex. The richness of contingencies is a property of human action, not a limitation of the contingency graph approach. An approach that allows and encourages analysts to make contingencies explicit, and does so with a formal representation that is amenable to computational support for analysis, is superior to one that does neither. Yet these colleagues' concern demonstrates the need for software support in retrieving information from and obtaining selective views of the contingency graph.

Future Work

The greatest practical need is to develop software tools to help construct and use the contingency graph. The need for improved analysis tools is a recurring theme (Sanderson & Fisher, 1994), and the size and density of potential data sets in the emerging ubiquitously connected world exacerbates this need. It is time consuming to construct a contingency graph manually. Initially, our contingency graphs were constructed using tools such as Excel™, Visio™, and Omnigraffle™. Early analyses took place over many months concurrently with extensive discussions in which we developed the theoretical and practical basis for the framework and revised the graphs multiple times. Subsequently, we conducted similar manual analyses of other sessions in several days. Customized software support can help address this problem by partially automating data collection and the construction of the graph through contingencies. Two prototype tools have been constructed: the Uptake Graph Utility described previously, and a tool for constructing and visualizing the reply structure of discussions in Tapped IN and CLTNet online communities. The present work has developed the initial representational specifications for further development of a shareable set of tools. These tools should enable access to contingency graphs at multiple granularities and through filters, compressing them in time and/or scanning for patterns. An analyst need not even use a graph representation at all: Visualization tools can convert the underlying graph model into any useful visualization. Other visual representations should be explored.

In ongoing work, we continue to apply the uptake analysis framework to a diversity of data in preparation for development of software support tools. Our objective is to speed up the analysis of intersubjective meaning making to the point where it need not be limited by tedious microanalysis, but can also be efficiently applied on a larger scale. An important aspect of evaluating this framework will be to determine how well it scales to larger groups across longer time scales. With improved automation it might be possible to generate contingency graphs for larger online communities over the course of months or even years. It remains to be seen whether the constructs of coordinations, contingencies, and uptake remain useful as the foundation for further analysis at these scales.

Boundary Objects for CSCL

The framework presented in this paper was developed to meet the immediate practical needs in our laboratory to support multi-method analyses of distributed interaction. However, this is only part of the story. We also had an additional motivation that to our surprise has turned out to be controversial, and, hence, left for the end of this paper so as not to detract from the primary contribution. We believe that the need for theoretical and methodological dialogue that we encountered in our own laboratory is a microcosm of a need that also exists in the CSCL community. Diverse lines of work exist in CSCL and allied endeavors: We study interaction in different media, examine phenomena ranging from micro-episodes in small groups to large communities over periods of weeks to months, and analyze data using various "qualitative" and "quantitative" analytic practices in studies framed by diverse and potentially incommensurate world views. This multivocality of CSCL is a strength, but only if there are "boundary objects" around which productive discourse can form (Star & Griesemer, 1989). Boundary objects "have different meanings in different worlds but their structure is common enough to more than one world to make them recognizable, a means of translation" (ibid, p. 393). Various candidates for such objects exist: For example, productive discourse might form around shared phenomena of interest, data sets, research questions, topic domains, and/or theories. Suthers (2006b) proposed the study of technology affordances for intersubjective meaning making as a focal phenomenon for CSCL, arguing that this topic distinguishes CSCL; is one on which we are best positioned to make progress; and that progress would inform not only our understanding of learning but other aspects of human activity as well. The work reported in this paper can be taken as a different basis for discourse in CSCL: a framework for representing data and conceptualizing interaction that unifies data from diverse sources and supports analytic practices from multiple traditions. Other researchers have constructed various specialized analysis and visualization tools to address the challenges of analyzing distributed interaction, but we suggest that a less ad hoc approach will further progress. Advances in other scientific disciplines have been accompanied with representational innovations, and shared instruments and representations mediate the daily work of scientific discourse (Latour, 1990). Similarly, researchers studying learning that takes place through interaction may benefit from shared ways of conceptualizing and representing the phenomena of interest as a basis for scientific and design discourse. Without these, it is difficult to build on each other's work except within homogeneous sub-literatures. We offer this framework to the research community in hopes it may support productive dialogue within the learning sciences. In doing so, we do not claim that a theoretically and methodologically unified field with one object of study is possible. Far from this, we do not even think it is desirable: Multivocality is a strength, and the value of boundary objects is based on this diversity. Rather, we advocate only for identifying common objects for productive discourse across what would otherwise be disjoint bodies of work, and herein propose further such objects.

Acknowledgments

The studies and analyses on which this paper is based were supported by the National Science Foundation under award 0093505. The work developed during years of intensive discussion among the authors that also benefited from interaction with numerous colleagues in our laboratory and elsewhere. We especially thank Gerry Stahl for his ongoing commentary on these ideas and the anonymous reviewers for comments that helped address problems with prior drafts.

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